Wine_Quality_Prediction

April 30, 2023

1 WINE QUALITY PREDICTION

11.0

13.0

Importing The Libraries

4

5

```
[1]: import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
[2]: from sklearn.model_selection import train_test_split
     from sklearn.ensemble import RandomForestClassifier
     from sklearn.metrics import accuracy score
    Read the csv file into a DataFrame
[3]: df=pd.read_csv('wine.csv')
[4]: df.head(10)
[4]:
        fixed acidity volatile acidity
                                          citric acid
                                                       residual sugar
                                                                         chlorides \
                  7.4
                                    0.70
                                                  0.00
                                                                    1.9
     0
                                                                              0.076
                                    0.88
     1
                  7.8
                                                  0.00
                                                                    2.6
                                                                              0.098
                  7.8
                                                                    2.3
     2
                                    0.76
                                                  0.04
                                                                              0.092
     3
                 11.2
                                    0.28
                                                  0.56
                                                                    1.9
                                                                              0.075
     4
                  7.4
                                    0.70
                                                  0.00
                                                                    1.9
                                                                             0.076
                  7.4
     5
                                    0.66
                                                  0.00
                                                                    1.8
                                                                             0.075
                  7.9
                                                  0.06
                                                                    1.6
     6
                                    0.60
                                                                             0.069
     7
                                                                    1.2
                  7.3
                                                  0.00
                                    0.65
                                                                             0.065
     8
                  7.8
                                    0.58
                                                  0.02
                                                                    2.0
                                                                              0.073
     9
                  7.5
                                                  0.36
                                                                    6.1
                                    0.50
                                                                             0.071
                                                     density
        free sulfur dioxide total sulfur dioxide
                                                                 Дq
                                                                    sulphates
     0
                        11.0
                                               34.0
                                                      0.9978
                                                               3.51
                                                                          0.56
     1
                        25.0
                                               67.0
                                                      0.9968
                                                               3.20
                                                                          0.68
     2
                        15.0
                                               54.0
                                                      0.9970
                                                               3.26
                                                                          0.65
     3
                                               60.0
                        17.0
                                                      0.9980
                                                               3.16
                                                                          0.58
```

34.0

40.0

0.9978

0.9978 3.51

3.51

0.56

0.56

```
7
                        15.0
                                                21.0
                                                       0.9946
                                                                3.39
                                                                            0.47
     8
                         9.0
                                                18.0
                                                       0.9968
                                                                3.36
                                                                            0.57
     9
                        17.0
                                               102.0
                                                       0.9978
                                                                3.35
                                                                            0.80
        alcohol
                 quality
            9.4
     0
     1
            9.8
                        5
     2
            9.8
                        5
     3
            9.8
                        6
                        5
     4
            9.4
                        5
     5
            9.4
            9.4
                        5
     6
     7
           10.0
                        7
     8
            9.5
                        7
     9
           10.5
                        5
[5]: df.shape
[5]: (1599, 12)
     df.isnull().sum()
[6]: fixed acidity
                               0
     volatile acidity
                               0
     citric acid
                               0
     residual sugar
                               0
     chlorides
                               0
     free sulfur dioxide
                               0
     total sulfur dioxide
     density
                               0
     рΗ
                               0
     sulphates
                               0
     alcohol
                               0
     quality
                               0
     dtype: int64
[8]: df.describe()
[8]:
            fixed acidity
                            volatile acidity
                                                citric acid residual sugar \
               1599.000000
                                  1599.000000
                                                1599.000000
                                                                 1599.000000
     count
     mean
                  8.319637
                                     0.527821
                                                   0.270976
                                                                    2.538806
     std
                  1.741096
                                     0.179060
                                                   0.194801
                                                                    1.409928
     min
                  4.600000
                                     0.120000
                                                   0.000000
                                                                    0.900000
     25%
                  7.100000
                                     0.390000
                                                   0.090000
                                                                    1.900000
     50%
                  7.900000
                                     0.520000
                                                   0.260000
                                                                    2.200000
     75%
                  9.200000
                                     0.640000
                                                   0.420000
                                                                    2.600000
```

59.0

0.9964

3.30

0.46

6

15.0

max	15.90000	0 1.	580000	1.00	00000 15	.500000	
	chlorides	free sulfur	dioxide 1	total	sulfur dioxid	e density	\
count	1599.000000	1599	.000000		1599.00000	0 1599.000000	
mean	0.087467	15	.874922		46.46779	0.996747	
std	0.047065	10	.460157		32.89532	4 0.001887	
min	0.012000	1	.000000		6.00000	0.990070	
25%	0.070000	7	.000000		22.00000	0.995600	
50%	0.079000	14	.000000		38.00000	0.996750	
75%	0.090000	21	.000000		62.00000	0.997835	
max	0.611000	72.000000			289.00000	0 1.003690	
	рН	sulphates	alcol	hol	quality		
count	1599.000000	1599.000000	1599.0000	000	1599.000000		
mean	3.311113	0.658149	10.4229	983	5.636023		
std	0.154386	0.169507	1.0656	668	0.807569		
min	2.740000	0.330000	8.4000	000	3.000000		
25%	3.210000	0.550000	9.5000	000	5.000000		
50%	3.310000	0.620000	10.2000	000	6.000000		
75%	3.400000	0.730000	11.1000	000	6.000000		
max	4.010000	2.000000	14.9000	000	8.000000		

[9]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):

#	Column	Non-Null Count	Dtype
0	fixed acidity	1599 non-null	float64
1	volatile acidity	1599 non-null	float64
2	citric acid	1599 non-null	float64
3	residual sugar	1599 non-null	float64
4	chlorides	1599 non-null	float64
5	free sulfur dioxide	1599 non-null	float64
6	total sulfur dioxide	1599 non-null	float64
7	density	1599 non-null	float64
8	рН	1599 non-null	float64
9	sulphates	1599 non-null	float64
10	alcohol	1599 non-null	float64
11	quality	1599 non-null	int64

 ${\tt dtypes: float64(11), int64(1)}$

memory usage: 150.0 KB

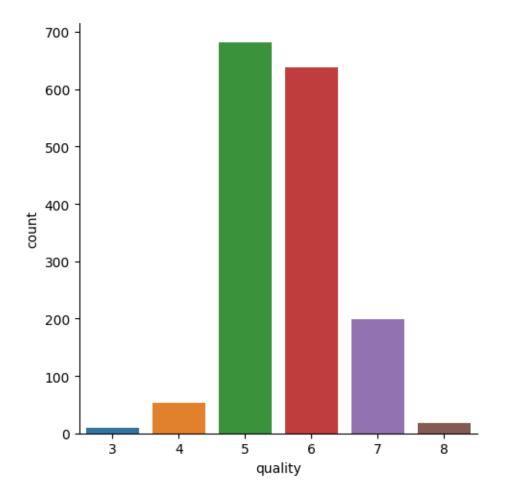
[10]: df.dtypes

[10]: fixed acidity float64 volatile acidity float64 citric acid float64 residual sugar float64 chlorides float64 free sulfur dioxide float64 total sulfur dioxide float64 density float64 float64 рΗ sulphates float64 alcohol float64 quality int64dtype: object

Visualization of Data

Number of values for each quality

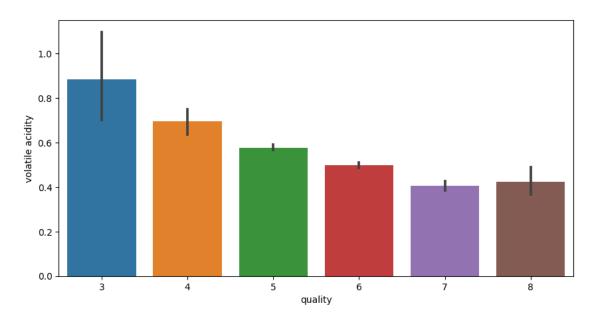
[16]: <seaborn.axisgrid.FacetGrid at 0x7feb6a606a70>



Volatile Acidity vs Quality

```
[18]: plot = plt.figure(figsize=(10,5))
sns.barplot(x='quality', y = 'volatile acidity', data = df)
```

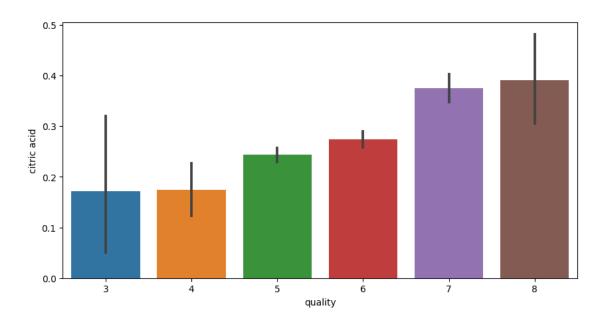
[18]: <Axes: xlabel='quality', ylabel='volatile acidity'>



Citric Acid vs Quality

```
[19]: plot = plt.figure(figsize=(10,5))
sns.barplot(x='quality', y = 'citric acid', data = df)
```

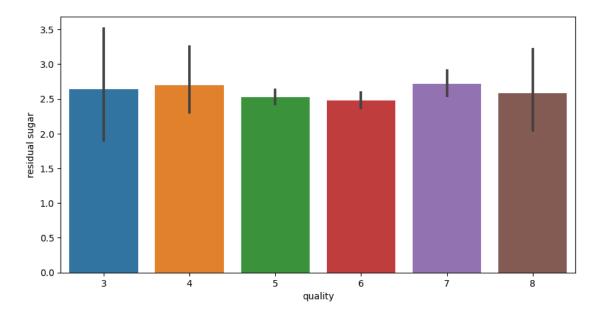
[19]: <Axes: xlabel='quality', ylabel='citric acid'>



Residual Sugar vs Quality

```
[20]: plot = plt.figure(figsize = (10,5))
sns.barplot(x = 'quality', y = 'residual sugar', data = df)
```

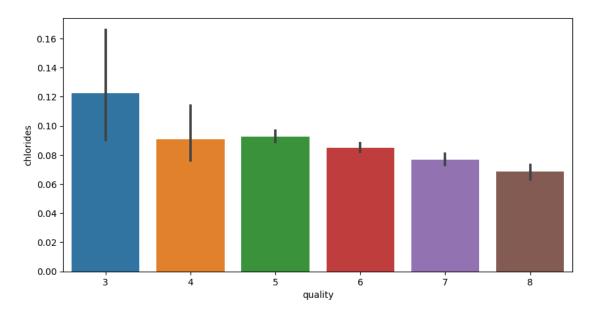
[20]: <Axes: xlabel='quality', ylabel='residual sugar'>



Chlorides vs Quality

```
[22]: fig = plt.figure(figsize = (10,5))
sns.barplot(x = 'quality', y = 'chlorides', data = df)
#Composition of chloride also go down as we go higher in the quality of the wine
```

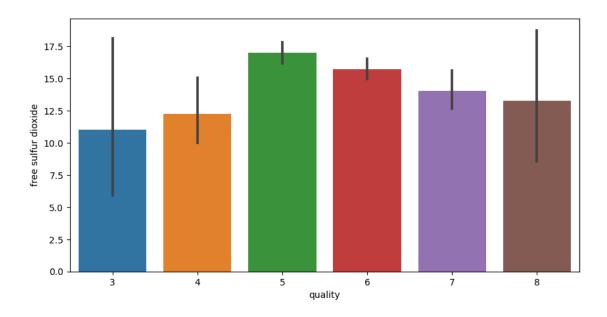
[22]: <Axes: xlabel='quality', ylabel='chlorides'>



Free Sulphur Dioxide vs Quality

```
[23]: fig = plt.figure(figsize = (10,5))
sns.barplot(x = 'quality', y = 'free sulfur dioxide', data = df)
```

[23]: <Axes: xlabel='quality', ylabel='free sulfur dioxide'>

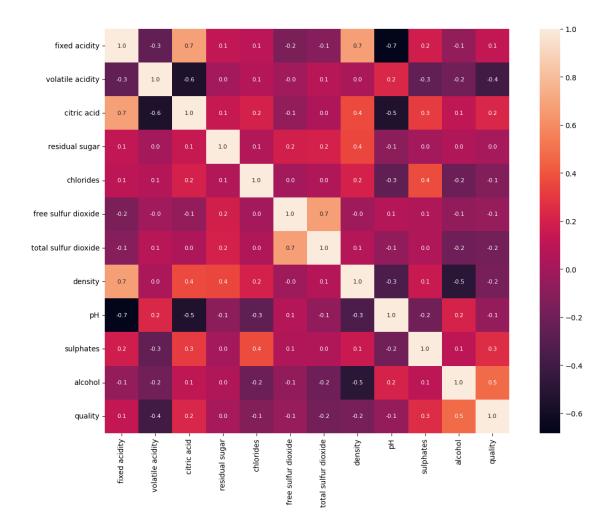


Correlation

```
[24]: Corr = df.corr()

[25]: plt.figure(figsize=(15,10))
sns.heatmap(Corr, cbar=True, square=True, fmt = '.1f', annot = True,
→annot_kws={'size':8})
```

[25]: <Axes: >



Data Preprocessing

Separate the Data and label

```
[26]: X = df.drop('quality',axis=1)
```

[27]: print(X)

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	\
0	7.4	0.700	0.00	1.9	0.076	
1	7.8	0.880	0.00	2.6	0.098	
2	7.8	0.760	0.04	2.3	0.092	
3	11.2	0.280	0.56	1.9	0.075	
4	7.4	0.700	0.00	1.9	0.076	
	•••	•••	•••			
15	94 6.2	0.600	0.08	2.0	0.090	
15	95 5.9	0.550	0.10	2.2	0.062	
15	96 6.3	0.510	0.13	2.3	0.076	

```
1597
                     5.9
                                      0.645
                                                    0.12
                                                                     2.0
                                                                              0.075
     1598
                     6.0
                                      0.310
                                                    0.47
                                                                     3.6
                                                                              0.067
           free sulfur dioxide total sulfur dioxide density
                                                                  pH sulphates \
                          11.0
                                                 34.0 0.99780 3.51
                                                                           0.56
     0
                          25.0
                                                 67.0 0.99680 3.20
                                                                           0.68
     1
     2
                          15.0
                                                 54.0 0.99700 3.26
                                                                           0.65
     3
                          17.0
                                                 60.0 0.99800 3.16
                                                                           0.58
     4
                          11.0
                                                 34.0 0.99780 3.51
                                                                           0.56
                          32.0
                                                 44.0 0.99490 3.45
                                                                           0.58
     1594
     1595
                          39.0
                                                 51.0 0.99512 3.52
                                                                           0.76
     1596
                          29.0
                                                 40.0 0.99574 3.42
                                                                           0.75
                          32.0
                                                 44.0 0.99547 3.57
                                                                           0.71
     1597
     1598
                          18.0
                                                 42.0 0.99549 3.39
                                                                           0.66
           alcohol
     0
               9.4
     1
               9.8
     2
               9.8
     3
               9.8
     4
               9.4
     1594
              10.5
     1595
              11.2
              11.0
     1596
     1597
              10.2
              11.0
     1598
     [1599 rows x 11 columns]
[28]: Y = df['quality'].apply(lambda y_value: 1 if y_value>=7 else 0)
[29]: print(Y)
     0
             0
     1
             0
     2
             0
     3
             0
     4
             0
     1594
             0
     1595
             0
     1596
             0
     1597
             0
     1598
     Name: quality, Length: 1599, dtype: int64
```

Train Test Split

```
[30]: X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,
       →random_state=3)
     Model Training
[31]: model = RandomForestClassifier()
[32]: model.fit(X_train, Y_train)
[32]: RandomForestClassifier()
     Evaluating The Model
     Accuracy on test data
[33]: X_test_prediction = model.predict(X_test)
      test_data_accuracy = accuracy_score(X_test_prediction, Y_test)
[34]: print('Accuracy: ', test_data_accuracy)
     Accuracy: 0.928125
[35]: | input_data = (7.5,0.5,0.36,6.1,0.071,17.0,102.0,0.9978,3.35,0.8,10.5)
     Changing the input data to a numpy array
[38]: input_data_to_numpy_array = np.asarray(input_data)
[39]: input_data_reshape = input_data_to_numpy_array.reshape(1,-1)
      #Here we are reshaping the data as we are predicting the label for only one_{f U}
       \rightarrow instance
     Prediction
[40]: prediction = model.predict(input_data_reshape)
      print(prediction)
      if (prediction[0]==1):
        print('Good Quality Wine')
```

[0]

else:

Bad Quality Wine

print('Bad Quality Wine')

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature

```
names
    warnings.warn(
[]:
```